Performance estimation method for gigabit passive optical networks using machine learning

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Gigabit passive optical network (GPON) has evolved into large data provider technique. Analysis of network-generated data is critical for efficient fault diagnosis and self-configuration in GPON. Machine learning-based data analytics technologies could be significant in analyzing the performance of these kinds of optical networks. So, a machine learning approach for estimating the performance of GPON is proposed in this paper. A dataset containing fiber length, transmission power, the number of power splitters, line width, and extinction ratio factors has been created in this work to assess the Q factor value for a specific optical network. Then, the relief attribute evaluation technique is used to pick fiber length, transmission power, and the number of power splitters from among given parameters. For predicting different levels of Q factor, these specific parameters are supplied into a regression-based tree classification model. This paper considers logistic regression, decision tree, decision table, PART, and random forest algorithms for estimating the performance of GPON. As per the simulation findings of the present work, the proposed regression-based tree classification technique gives an effectual approximation of the Q factor with the accuracies of 93.8 % and 96.41% for seven-class and three-class cases respectively. As a result, the proposed approach appears to be a good fit for accurately estimating the performance of GPON.

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Keywords: Gigabit passive optical network, Machine Learning, Classification, Q factor, Performance estimation

1. Introduction

The surge in demand for video, IPTV, and video conferencing is illustrating the rise in Internet popularity. Large bandwidth and consistent long-distance data transmission are necessary to fulfil these demands, which can be provided via passive optical networks (PON) [1]. Generally, a point-to-multipoint network is referred to as a PON, which is often a tree topology. PONs are a collection of prospective broadband access network technologies those give considerable benefits when installed in fiber-to-the-home (FTTH) circumstances. Their advantages include a point-to-multipoint design, high-quality triple-play service abilities for data, phone, and video, high-speed internet access, and other cost-effective services [2,3]. As per the International Telecommunications Union (ITU) and the Institute of Electrical and Electronics Engineers (IEEE), the major four categories of PONs include ATM PON (APON), Broadband PON (BPON), and Gigabit PON (GPON) and Ethernet PON (EPON). Among all, Gigabit PONs have emerged as one of the leading passive optical networks for providing seamless services to subscribers [9].

Like other optical networks, GPONs also convey huge volumes of data from a number of sources, such as customer behavioural statistics, network traffic traces, signal quality indicators and network alarms etc. [3,5]. Advanced mathematical approaches are required to extract useful information from this data and to make choices regarding the proper functioning of networks on the basis of the obtained information. Among these tools, machine learning (ML) is one of the most promising methodological approaches for performing network-data analysis and allowing autonomous network self-configuration and fault management [6]. The significant rise in network complexity that optical networks have undergone in recent years has motivated the adoption of machine learning techniques in optical communication networks [7,8].

A few examples of the usage of ML techniques in these optical networks include the tensor flow-based traffic analysis of GPON using various machine learning algorithms by Oujezsky et al. [10]. Similarly, Tomasov et al. [11] presented a supervised neural network-based analysis of messages related to physical layer operations, administration and maintenance downstream of GPONs to interpret the discrimination among them. Echraibi et al. [12] also discussed machine learning-based deep infinite mixture models to detect and interpret faults occurring in GPONs. In addition, Liu et al. [13] proposed a machine learning-based equalization technique for GPONs, which made use of k-nearest neighbour (kNN) classifier to optimize the equalization performance for expanding the bandwidth of GPONs. Moreover, Butt et al. [14] made use of machine learning for load balancing and dynamic bandwidth allocation in time and wavelength division passive optical networks.

In continuance of the use of machine learning in the domain of optical communication, the current study proposes a unique machine learning-based technique for estimating the performance of GPONs. To estimate the Q factor for a specific GPON, a dataset comprising optical network metrics such as fiber length, transmission power, the number of power splitters, line width, and extinction ratio factors was constructed. Among these network metrics, the number of power splitters, fiber length, as well as transmission power are determined using the relief attribute selection approach. The dataset of these three-input metrics has been put into a regression-based tree classification model to calculate varying Q factor values. This research also analyses other machine learning models such as logistic regression, decision tree, decision table, PART, and random forest algorithms for the required purpose. The regression-based tree classification model approach provides an effective estimation of Q value for 7-class and 3-class cases, according to simulation outcomes. As a consequence, this method looks to be an excellent fit for properly estimating the performance of GPONs.

This paper is divided into several sections. The first section introduces passive optical networks, the requirement for machine learning in analyzing and optimizing the performance of these networks, and the suggested technique for this assignment. In part 2, the GPON architecture, simulation setup, and parameters are addressed. The usage of machine learning algorithms for the classification of a given GPON dataset into different Q factor classes has been elaborated in the results and discussion section, which is section 3 of the present paper. Finally, conclusions are drawn from the outcomes of the simulation work, which are mentioned in section 4.

2. Methods and materials

The suggested GPON architecture, its simulation setup, and the production of a dataset for the estimate of Q factor for performance prediction are discussed in this section. This section also goes over the attribute selection criterion for identifying essential input parameters in a dataset and classifying them using various machine learning methods. The next sub-sections go through each of these processes in further detail.

2.1. Overview of Gigabit passive optical network (GPON)

ITU-T has standardized GPON (Gigabit Capability Passive Optical Network) with Recommendation G.984.1, 2, 3, 4, and 5 [9]. Voice, TDM (Time Division Multiplex), Ethernet, ATM (Asynchrony Transport Mode), shared line, wireless extension, and other services are all supported by GPON. Furthermore, GPON offers symmetrical 622 Mbit/s downstream and symmetrical 1.25 Gbit/s upstream, both of which employ the same protocols. As a result, GPON is a technology that is well-suited to triple-play services [9].

The FTTH (Fiber to the Home) network architecture is one of the most widespread GPON network topologies. Asymmetric and symmetric broadband services, POTS (Plain Old Telephone Service) and ISDN (Integrated Service Digital Network), as well as narrowband services such as phone lines, are all examples of this type of design. The most popular downstream and upstream speeds in GPON are 2.4Gbit/s and 1.2Gbit/s [15].

The GPON network can be divided into five sections. The aggregation switch is the first component, and it is responsible for receiving traffic from the uplink transport section while filtering out superfluous traffic [17]. Part 2 talks about OLT, which is a crucial part of GPON. It can be considered the "brain" of a GPON network. Traffic scheduling, buffer control, and bandwidth allocation are the three most significant activities performed by OLT [16]. The optical distribution network is the third part. It is a traditional optical network with a few extra splitters. PON tree network architecture is used in GPON since it is a sort of PON network. The following is the design of this architecture: one optical fiber is connected to a GPON port (OLT), and all users are connected to it. GPON classes A, B, B+, C, and C+ are used to define ODN (Optical Distribution Network). The most common today is class B+, which permits a signal to be split up to 64 times for 64 users across a distance of up to 20 kilometers [15]. Part 4 is a GPON network's distant end (ONU – Optical Network Unit), and as stated in the text above, the number of GPON endpoints varies depending on which classes are employed; in the case of B+, the number is 64. Each GPON end can have several ports (UNI – User-Network Interface); in the case of GPON, the ONU is referred to as an ONT. The user equipment is represented in Part 5. It might be a traditional phone, a PC, or a Setup Box for residential customers. The chapter will demonstrate how SNI (Service Network Interface) can be used to connect to an ONU/ONT (Optical Network Terminal) [16,18].

A diagram of GPON architecture and features can be found in Fig. 1. Its capabilities are comparable to those of BPON and EPON schemes. GPON architecture, on the other hand, has an advantage over BPON and EPON designs. This benefit might be attributed to the fact that the GPON operational scheme is more customer-centric in design [19].

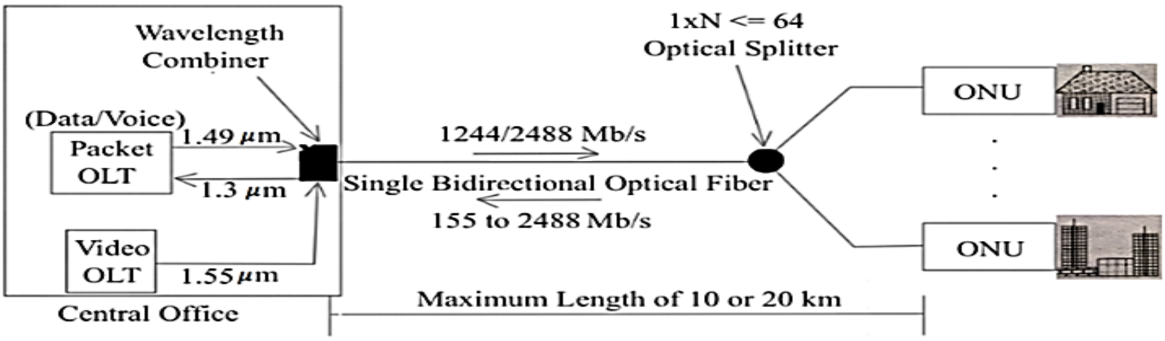

Fig. 1. GPON architecture [9]

The capabilities of GPON are similar to those of BPON and EPON schemes. GPON architecture, on the other hand, has an advantage over BPON and EPON designs. This benefit might be attributed to the fact that the GPON operational scheme is more customer-centric [9]. The G.984 [9] was certified by the ITU-T in March 2003. The GPON structure, desired bit rates, optical power splitting ratios, types of services to be performed, information security, and signal transfer delays are all covered in this recommendation [9]. Some requirements of the BPON G.983 guidelines are maintained by G.984 in order for the GPON model to be compatible with the BPON model.

2.2. GPON simulations

Fig. 1 depicts the simulation setup that is used to analyze the system's performance in both downstream and upstream traffic. The performance of a certain GPON architecture is examined using the Optisystem 13.0 software in this study [20]. The downstream and upstream data are sent at wavelengths of 1490 nm and 1500 nm, respectively. The CW laser, non-return-to-zero (NRZ), return-to-zero (RZ), optical circulator, single optical fiber, Erbium-Doped Fiber Amplifier (EDFA), and bit error rate (BER) analyzer are among the components utilized in this configuration. Table 1 shows the total parametric values changed in the optical simulation setup based on conventional network values. Downstream traffic is sent across an optical fiber with a wavelength of 1490 nm, a length of 0 to 50 kilometers, the transmission power of -5 to 5 dBm, and power splitter with split ratios of 8, 16, 32, 64, 128.

Table 1. Parameters and its ranges

Parameter	Value
Fiber length	0 to 50 km
Frequency	1490 nm
Transmission power	-5 to 5 dBm
Power splitter	8,16,32,64,128
Line width	10 MHz
Extinction Ratio	15db
Attenuation	0.25 dB/km

2.3. GPON simulation dataset

Five primary network metrics were taken into account in this study: fiber length, transmission power, extinction ratio, line width, and power splitters, in order to generate a dataset for examining the performance of GPON in terms of Q value estimates. Downstream traffic is carried by an optical fiber with a length of 0 to 50 kilometers and a wavelength of 1550 nm. Extinction Ratio of 15dB to 16 dB, line width of 10MHz, and transmission power of -5 to 5 dBm are the other numbers. Because the current model assumes a total of 128, the power splitters taken into account have values of 8,16,32,64, and 128. Q factor estimations were produced using various combinations of values for these input parameters. As a result, a dataset of 23000 data samples was created. Table 2 shows some of these data samples.

Table 2. Dataset of GPON

Fiber Length	Transmission Power	Line Width	ER	Power Splitters	Q Factor
46	-4.16667	15.1856	10	8	0
31.5	0.208333	15.1258	10	64	1.51
20	-1.875	15.0784	10	64	1.76
50	4.79167	15.2021	10	64	2.01
40.5	3.75	15.1629	10	64	3.01
29.5	-3.75	15.1175	10	8	5.13
25	-0.83333	15.099	10	16	6.92
18.5	4.16667	15.0722	10	64	7.02
10.5	-4.16667	15.0392	10	8	12.7
22.5	1.66667	15.0887	10	16	12.9
8.5	5	15.0309	10	64	16.9
20	1.875	15.0784	10	16	19.0
22	3.95833	15.0866	10	16	23.9
14	1.875	15.0536	10	16	25.6
5.5	-0.41667	15.0186	10	8	38.9
8	0.833333	15.0289	10	8	50.2
10	3.125	15.0371	10	8	67.9
12	3.95833	15.0454	10	8	73.7
10.5	4.375	15.0392	10	8	85.3
9.5	3.54167	15.0351	10	8	89.4
6.5	3.95833	15.0227	10	8	91.3
4.5	3.75	15.0144	10	8	95.68
10.5	4.79167	15.0392	10	8	100.65
6.5	4.58333	15.0227	10	8	112.94
5	4.58333	15.0165	10	8	127.42
5.5	4.375	15.0186	10	8	132.65
6	5	15.0206	10	8	142.04
1.5	5	15.0021	10	8	151.47
1	5	15	10	8	160.73

The input dataset must be categorized by distinct classes in order to use machine learning-based classification techniques. In this dataset, the values of the Q factor are used as output class labels, which are further separated into two types. The Q factor values in the first set are divided into seven classes, whereas the Q factor values in the second set are divided into three classes. Table 3 shows the categorization information for seven classes, whereas Table 4 shows the categorization information for three classes.

Table 3. Seven class classification of Q factor

Q Factor Range	Output Class
0 to 9	Zero
10 to 19	Ten
20 to 29	Twenty
30 to 39	Thirty
40 to 49	Forty
50 to 59	Fifty
60 and above	Sixty

Table 4. Three class classification of Q factor

Q Factor Range	Class
0 to 6	Non-satisfactory
7 to 13	Satisfactory
13 and above	Effective

2.4. Selection of significant parameters

The attribute evaluator is a mechanism for evaluating each attribute in a dataset in terms of the output classes. There will be some attributes in a database with a big number of attributes that do not become significant in the analysis you are now seeking [21]. As a result, discarding undesirable attributes from the dataset would become a critical step in establishing a better machine learning model. The current work employs the Relief Attribute Evaluation approach to accomplish this goal [22]. It calculates the value of an attribute by sampling an instance multiple times and comparing the value of the supplied attribute for the closest instances of the same class as well as other classes. The reason for employing this approach is that it is an efficient method having good perception of contextual information of given data. Moreover, it also has ability to precisely estimate the quality of features in cases having strong dependencies among features [22]. As shown in Table 5, the Relief attribute evaluation model evaluates the given input features of the given GPON dataset on a scale of 0 to 1 in this study.

Table 5. Ranking of input parameters for GPON using Relief attribute evaluation technique

Rank	Input Parameter	Rank Value
1	Power Splitter	0.3
2	Transmission Power	0.26
3	Fiber Length	0.1
4	Extinction Ratio	0.04
5	Line Width	0.01

It is clear from this table that this attribute assessment method gives the highest priority to the power splitter, followed by transmission power and fiber length. Extinction ratio and line width, on the other hand, are ranked at 4 and 5, respectively, with marginal values of their ranks, resulting in their elimination. As a result of this technique, the most essential input variables for estimating the performance of BGPON in regards to Q factor estimates are the power splitter, transmission power, and fiber length.

2.5. Classification

The present work makes use of Weka software tool package for the classification of different Q factor classes using various machine learning (ML) classifiers [23]. Various ML classifiers utilized in this work include regression tree-based classification model (also known as classification via regression) (M5P) [24, 25], decision tree (J48) [26], logistic regression [27], decision table [28], PART [29], and random forest [30] algorithms. In the current work, the supplied GPON dataset has been partitioned into training and testing sets for this objective, with 90% samples for training and 10% samples for testing the machine learning algorithms.

3. Results analysis and discussions

The simulation results of several ML classifiers on specified GPON datasets are described in this section. It also includes an evaluation of the findings in order to develop conclusions regarding the most appropriate classifiers for estimating GPON performance. As previously stated, the current study uses six machine learning classifiers to perform the task of classifying different Q factor classes in a specified GPON dataset. Logistic regression (LR), decision tree (J48), classification by regression (M5P), decision table, PART, and random forest are among the classifiers available. This classification assignment is carried out in two stages. The classification has been carried out in the first phase utilizing specified classifiers for seven distinct classes of Q factor, i.e., Q factor values of 0, 10, 20, 30, 40, 50, and 60. This technique is also repeated in the second phase for a three-class situation with three classes of Q factor, namely, non-satisfactory, satisfactory, and effective. To implement classification in both phases using given ML classifiers, 10-fold cross validation approach has been taken into consideration for generalized classification. Various performance measures, including accuracy, precision, recall, an area under the curve (AUC), and F-measures, have been used to assess the classification efficiency of these classifiers.

3.1. Analysis of results for seven class classification of Q factor estimates

Table 6 depicts the classification performance of various ML classifiers in terms of accuracy, precision, recall, AUC, and F measure for estimating three different Q factor classes of given GPON. With the exception of the logistic regression model, all ML classifiers offer good results with accuracy values above 90%. In the table following short names have been used for the classifiers, L.R: Logistic Regression, D.T: Decision Tree (J48), R.T.C: Regression-Tree Classification, D.T: Decision Table, R.F: Random Forest, P: PART.

Table 6. Performance evaluation of GPON using different ML classifiers for seven-class classification of Q factor estimates

Performance Measures	L.R	D.T (J48)	R T C (M5P)	D.T	P	R.F
Accuracy (%)	78.92	93.05	93.8	90.75	92.93	93.3
Precision (%)	75.4	93.0	93.7	90.5	92.9	93.3
Recall (%)	78.9	93.1	93.8	90.8	92.9	93.3
AUC (%)	90.1	98.6	99.7	97.9	98.5	99.2
F-Measure	76.4	93.0	93.7	90.6	92.9	93.3

According to this table, the regression tree classification model (M5P) model has the highest accuracy value of 93.8%, preceded by random forest, decision tree, PART, decision table, and logistic regression, which have accuracies of 93.3%, 92.05%, 92.93%, 90.75%, and 78.92% respectively. So, a logistic regression classifier with a minimum value of accuracy is not suited for accurate classification of Q factor levels. In addition, the M5P classifier offers 93.7% precision, 93.8% recall, 99.7% AUC, and 93.7% F measure values, which are maximum among other classifiers, thereby making it a suitable option for the given task of estimating the performance of GPON.

The performance of the regression tree-based classification (M5P) model has also been evaluated by looking at the precision, recall, AUC, and F measure values for each of the seven Q factor classes of GPON individually, as shown in Fig. 2. M5P model yields precision ranging from 53.7% for the 'Fifty' class of Q factor estimate to a maximum of 98.7% for the 'Zero' class of Q factor estimation, as illustrated in this figure. The proposed classifier has a minimum recall of 30.9% for the 'Fifty' class and a maximum recall of 98.7% for the 'Zero' class of Q factor. Furthermore, it specifies the minimum AUC of 99% for class 'Twenty' and a maximum AUC of nearly 100% for class 'Sixty'. This classifier, too, has a minimum F measure of 39.7% for class 'Fifty' and a maximum F measure of 98.7% for class 'Zero'. The greater value of AUC across all Q factor classes, as seen in this figure, demonstrates the effectiveness of the suggested classification model.

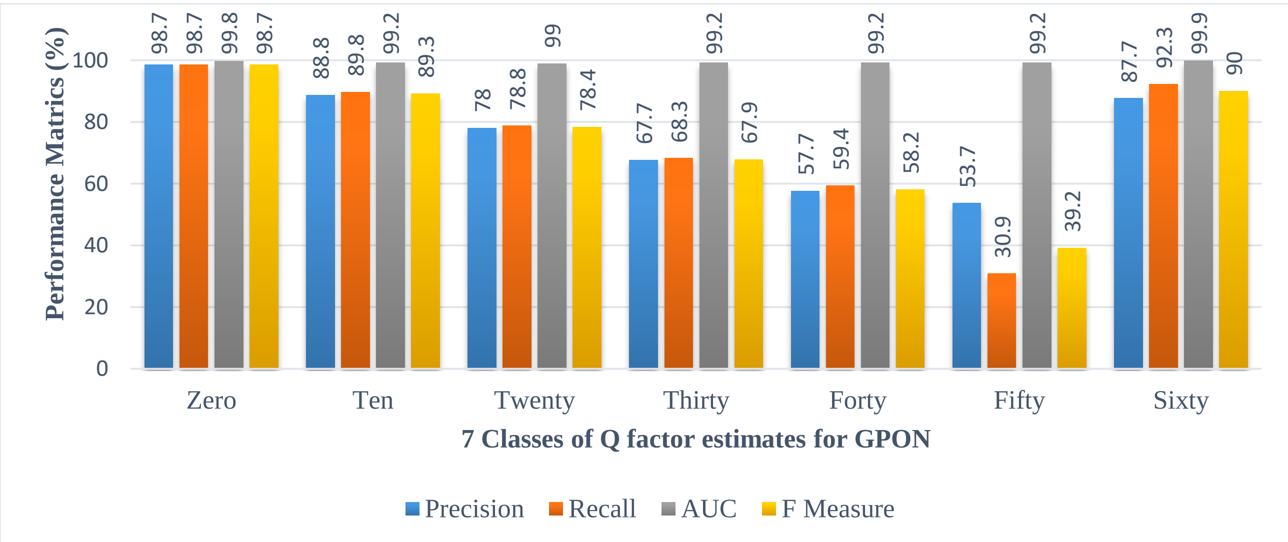

Fig. 2. Performance of regression-tree based classification model in terms of precision, recall, AUC and F measures for seven classes of Q factor (color online)

3.2. Analysis of results for three-class classification of Q factor estimates

Similarly, the performance of several ML models has been assessed for three Q factor classes: non-satisfactory, satisfactory, and effective. As stated in Table 7, the outcomes of the given classifiers were assessed in terms of average values of several performance metrics. With a maximum accuracy of 96.41%, regression-based tree classification model (M5P) performs better than all other classifiers, as seen in this table. PART, decision tree, random forest, and decision table models possess accuracies of 95.92%, 95.9%, 95.76%, and 92.2% respectively. Logistic regression offers a minimal accuracy of 71.4% in this situation of three-class categorization, making it inappropriate for precise estimation of BPON functionality. Moreover, among other machine learning models, the M5P model achieves maximum average precision of 96.4%, maximum recall of 96.4%, maximum AUC of 99.7%, and maximum F measure of 96.4%, making it a suitable choice for performance estimation of Gigabit passive optical networks. Fig. 3 displays the performance of the proposed M5P model in terms of accuracy, recall, AUC, and F measure values of three classes of Q factor independently.

Table 7. Performance evaluation of GPON using different ML classifiers for three-class classification of Q factor estimates

Performance Measures	L.R	D.T (J48)	R T C (M5P)	D.T	P	R.F
Accuracy (%)	71.40	95.9	96.41	92.72	95.92	95.76
Precision (%)	73.0	96.0	96.4	92.6	95.9	95.8
Recall (%)	71.4	96.0	96.4	92.7	95.9	95.8
AUC (%)	85.0	98.9	99.7	98.4	99.3	99.4
F measure (%)	64.9	96.0	96.4	92.6	95.9	95.8

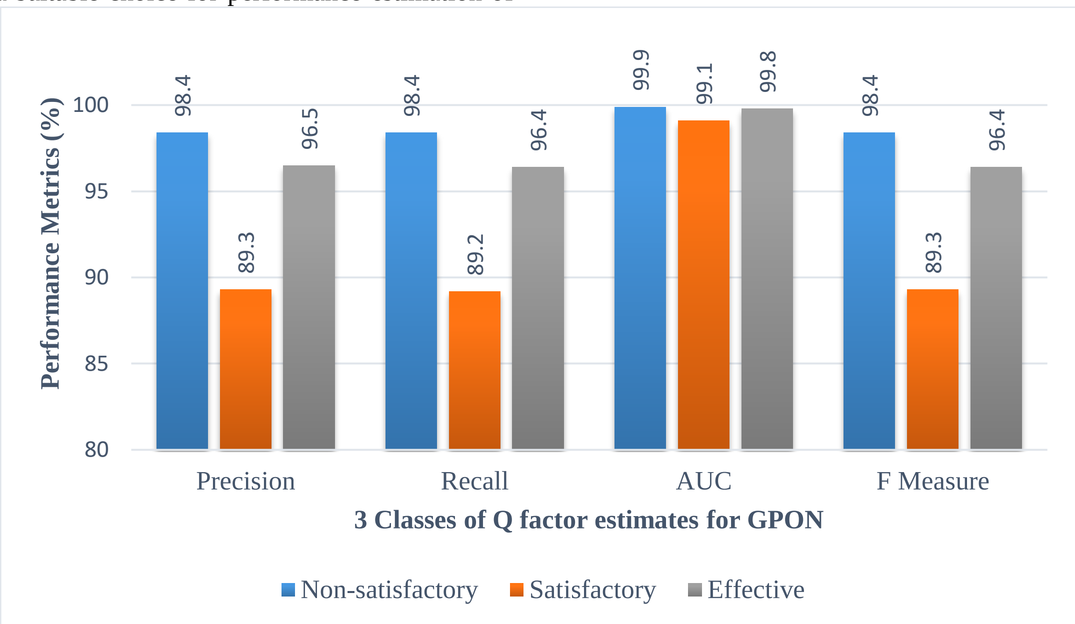

Fig. 3. Performance of regression-tree based classification model in terms of precision, recall, AUC and F measures for three classes of Q factor (color online)

M5P model has a precision of 98.4% for the 'Non-satisfactory' class, 96.5% for the 'Effective' class, and 89.3% for the 'Satisfactory' class, according to this graph. In the instance of recall, the suggested ML model offers a maximum average value of 98.4% for the 'Non-satisfactory' class, followed by 96.4% and 89.2% for the 'Effective' and 'Satisfactory' classifications respectively. Furthermore, for the 'Effective' and 'Non-satisfactory' classes, this classifier provides a maximum AUC of 99.9%, 99.8% and 99.1% for the and 'Non-satisfactory' , 'Effective' and 'Satisfactory' classes of Q factor for GPON performance estimation. This classifier, too, has a maximum F measure of 98.4% for 'Non-satisfactory,' 96.4% for 'Effective,' and 89.3% for 'Satisfactory' Q factor classes. As a result of this debate, it is evident that the suggested model is capable of identifying all three classes of Q factor accurately.

As a whole, the simulation results of various classification techniques in terms of the different performance metrics for three-class and seven-class classification of the Q factor clearly show that the proposed regression-based tree classification model (M5P) is a promising strategy for reliable and accurate estimation of the performance of Gigabit passive optical networks.

4. Conclusion

This research employs a machine learning approach to estimate the performance of broadband passive optical networks. To create an accurate prediction of Q factor, this method uses a dataset of essential network statistics. Fiber length, transmission power, and power splitters are among the network parameters identified utilizing the Relief attribute evaluation method for this study. Following that, the input samples of these attributes annotated with a certain Q factor class are supplied to various Machine learning models, such as logistic regression, decision tree, decision table, random forest, and PART. When these classifiers are compared on the basis of different performance metrics, it is clear that the regression-based tree classification model delivers the highest accuracy of 93.8% and 96.41 for seven-class and three-class Q factor estimation cases, respectively. As a result, it is concluded that the suggested regression-based tree classification model with selected significant network parameters is an efficient approach for reliably estimating the performance of GPONs in terms of Q factor values.

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